# Indoor Localization of a Mobile Object via Zigbee-Based RSSI

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***Abstract*—Being able to accurately track a moving object has been one of the main challenges in smart building applications. In this paper, an indoor localization technique for a mobile object using Zigbee-based Received Signal Strength Indication (RSSI) is considered. In order to alleviate the multipath effects from surrounding, a method utilizing the smoothness index to select RSSI values with best quality is proposed. The proposed strategy is evaluated via a simple experiment where the object with a receiver antenna is placed on a wheeled mobile robot moving on a predefined trajectory at a constant speed. The result is also compared with other standard filtering approaches, and the performance is analysed in terms of position error at each time instance between the initial and final positions of the object. Experimental results show that the cumulative error can be significantly reduced as compared to the results from other standard approaches.**

***Index Terms*—Zigbee, indoor localization, RSSI**

## I. Introduction

Wireless sensor network (WSN) has been an active research area for the past few decades. As the name suggests, WSNs are made up of a number of sensors in certain topology and infrastructure that make them fit for various applications. The most common use of WSNs is smart building applications as well as environmental monitoring from remote areas such as temperature, contamination level, humidity, light and motions [1].

Location estimation or localization, which is another common application of WSNs, is usually performed using Radio Frequency (RF) technique as the associated signal strength is easily obtained during the wireless transmission. This is particularly useful for indoor navigation and tracking in which the Global Positioning System (GPS) satellite navigation fails to operate. The RF technique, also termed as Received Signal Strength Indication (RSSI) method, is typically used to estimate the distance between two sensor nodes, or transmitter and receiver. There are few ways to find the position by using the RSSI such as trilateration algorithm, maximum likelihood algorithm, least square algorithm and location fingerprint positioning method [2].

The trilateration algorithm uses distances from nodes with known position and calculate the intersection of distance to find the unknown position. The maximum likelihood algorithm, on the other hand, approximates the location of a node by reducing the differences between the measured distances and estimated distances [3]. The least square algorithm uses distance from known position and roughly predict the position of unknown node, while the location fingerprint positioning method uses data from database and preliminary analytical model or specific orientation to calculate the position of the unknown point [4].

Typical RF-based localization technologies such as bluetooth, Wi-Fi, ultra-wide band (UWB) and Zigbee, have been extensively studied over the past decades [5]. Approaches via RSSI are always used with these technologies as they in general have the advantage of low cost and easy implementation. Nevertheless, they are bound to be disturbed by many environment factors such as multipath interference, refraction, electromagnetic field polarisation, and reflections from metallic objects. The Zigbee-based RSSI also become unstable in dynamic condition due to the narrower band which greatly affected by multipath fading [6]. In this regard, the RSSI method is often found to be less precise than other non-RF methods. To alleviate this main issue, RSSI readings are usually combined with filters or artificial intelligence to increase the accuracy. Some comparisons on these techniques can be found in [7], [8].

Most previous works on RSSI-based localization are concentrating on the error in position, which is the average distance between the located position and the real position. Plus, for moving objects, only the final positions are considered in performance evaluations. In other words, at each time instance, between the initial and final positions of the moving object, the error is not taken into account. In this paper, we evaluate the position error of the moving object at each time instance between the initial and final positions of the object. An improved algorithm for the Zigbee-based RSSI measurement is proposed by using average number of selected maximum RSSI observations. In this strategy, the smoothness index technique [9] is employed to evaluate the quality of the RSSI values. Experimental results show that by using the proposed strategy, the error of the moving object with respect to time can be significantly reduced as compared to the standard filtering approaches.

## II. Methodology

The dynamic range, accuracy, linearity and averaging period are the four parameters related to RSSI. The dynamic range is the minimum and maximum received

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signal energy that the receiver able to measure. The RSSI accuracy is the average error that each measurement can have. The RSSI linearity is the maximum deflection in the plot of RSSI in logarithmic scale between straight line and actual signal strength. Lastly, the RSSI is obtained after the received signal strength is measured for a certain amount of time and averaged. Due to the existence of steady state and dynamic environment the mean RSSI does not give the accurate picture of situation.

In indoor localization, there are few factors that cause the RSSI observations to fluctuate and become irregular. First, the presence of wall and other objects causes multipath interferences while the obstructions present between the receiver and transmitter causes RSSI causes shadowing. The presence of same frequency band devices affects the RSSI value by causing co-channel interference. The maximum RSSI value is proposed to make use of in the localization as it is the least affected by the factors mentioned and produces better localization accuracy. The averaging of the maximum RSSI is done to decrease effect of fading and reduce any instability of single maximum RSSI [10]. The number of maximum RSSI values used to average, $M$ is determined by using an empirical method presented in the next subsection.

### *A. Distance Estimation*

Radio signal encounters different degree of loss when it travels in the air. The loss or decay of received signal strength increases with distance travelled. There are several path loss models available such as Hatha, free space propagation, logarithmic distance path loss and logarithmic-normal distribution models [11]. These are used to calculate the degree of decay and eventually the distance the signal travelled. In this work, the logarithmic distance path loss model is selected as it consists of several parameters that can be tuned to make it fit in a pre-specified environment. The RSSI, $R$ (in dBm) in this model [12] is given by

$$R = 10n\log_{10}(d) + C \tag{1}$$

where $d$ (in meter) is the distance between the transmitter and the receiver, $n$ is the path-loss exponent, and $C$ is the RSSI value at 1 m away from the transmitter. The distance, $d$ can then be retrieved with:

$$d = 10^{\frac{R-C}{10n}} \tag{2}$$

The performance of the localization is affected by the type of signal extraction algorithm used. In order to supress the effects from propagation loss, we use a curve smoothness index, S, as in the equation below [10]:

$$S = \sum_{i=2}^{N-1}\sqrt{\left(R_i - \frac{R_{i-1}+R_i+R_{i+1}}{3}\right)^2} \tag{3}$$

where $N$ is the number of sample points on the curve, $R_i$ = RSSI value after being averaged with $M$ number of maximum RSSI values at the $i$th position.

The principle is that the smaller the value of $S$, the smoother the curve is, and the better the accuracy of the localization. In order to track a mobile object, however, the tracking speed is of particular importance. Thus, it is crucial to select an appropriate value of $M$.

In this work, a moving object is represented by a differential drive mobile robot. The localization of the object at each time instance is recorded as it moves on a straight line trajectory with a speed of around 30 cm/s. The experiment was carried out on a floor with 2m×2m dimension, a node (router) was placed at each vertex as shown in Fig. 1. The value $N$ was set to 11, and $R$ was collected by the router placed on the robot while moving.

Fig. 2 shows the effects of increasing $M$ on the smoothness index, and it is evident that the smoothness index of each individual node varies differently for different M values. This shows that the smoothness index does not have a uniform trend when $M$ is increased. To select the best possible value of $M$, the sum of all the smoothness indices from the four nodes, $S_{\text{sum}}$ is considered. The variation of $S_{\text{sum}}$ against $M$ is depicted in Fig. 3, and it shows that $S_{\text{sum}}$ is minimum when $M = 8$.

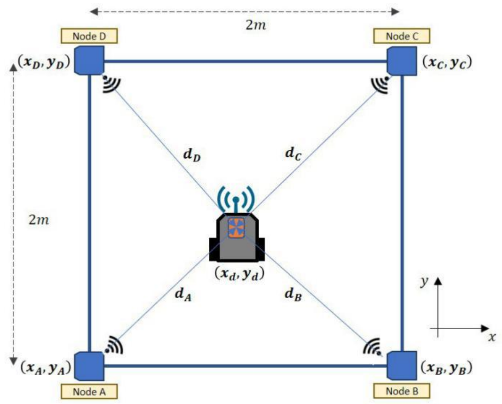


Fig. 1. Illustration on the experimental setup.

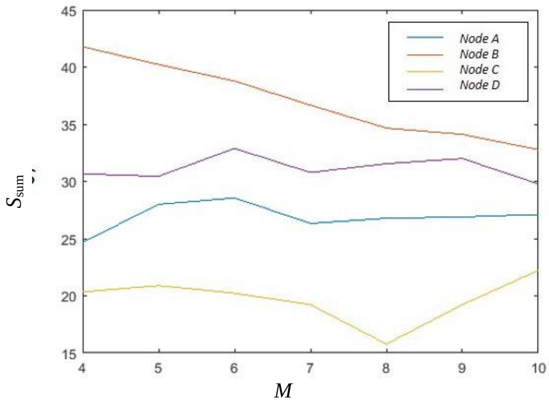


Fig. 2. Smoothness index of individual node against $M$ ,

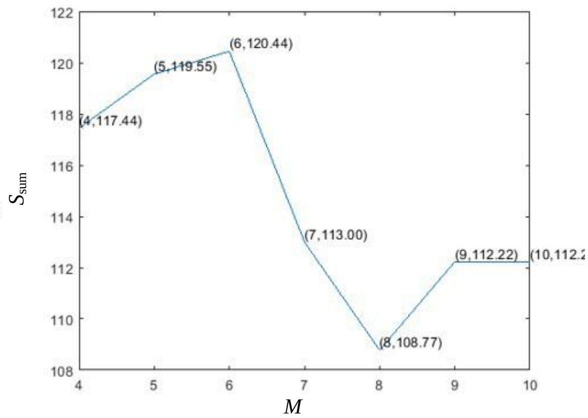


Fig. 3. Sum of all four smoothness indices against $M$.

### B. Localization of a Moving Object

In order to estimate the coordinate of the mobile object, few assumptions are made; (i) the coordinates of the nodes are known and fixed at the vertices as in Fig. 1, (ii) the antennas' positions for all nodes and the robot are fixed, (iii) at least three values of $R$ from three different nodes are received by the robot at a time.

The trilateration method is then used where we first need to calculate the corresponding distance values from the nodes to the robot using (2). Let $(x, y)$ be the unknown coordinate of the robot, and $(x_j, y_j)$ with $j = 1, 2, 3$ be the first three coordinates from three different nodes received by the robot. A simple Euclidean distance calculation gives

$$(x - x_1)^2 + (y - y_1)^2 = d_1^2 \tag{4}$$

$$(x - x_2)^2 + (y - y_2)^2 = d_2^2 \tag{5}$$

$$(x - x_3)^2 + (y - y_3)^2 = d_3^2 \tag{6}$$

Expanding these, we get

$$x^2 - 2x_{1x} + x_1^2 + y^2 - 2y_{1y} + y_1^2 = d_1^2 \tag{7}$$

$$x^2 - 2x_{2x} + x_2^2 + y^2 - 2y_{2y} + y_2^2 = d_2^2 \tag{8}$$

$$x^2 - 2x_{3x} + x_3^2 + y^2 - 2y_{3y} + y_3^2 = d_3^2 \tag{9}$$

Subtracting the second equation from the first leads to

$$\begin{aligned}(-2x_1 + 2x_2)x + (-2y_1 + 2y_2)y \\ = d_1^2 - d_2^2 + x_1^2 - x_2^2 + y_1^2 - y_2^2\end{aligned} \tag{10}$$

Applying the same method to the second and third equations gives

$$\begin{aligned}(-2x_2 + 2x_3)x + (-2y_2 + 2y_3)y \\ = d_2^2 - d_3^2 + x_2^2 - x_3^2 + y_2^2 - y_2^3\end{aligned} \tag{11}$$

Let

$$A_1 = -2x_1 + 2x_2,\ A_2 = -2x_2 + 2x_3 \tag{12}$$

$$B_1 = -2y_1 + 2y_2,\ B_2 = -2y_2 + 2y_3 \tag{13}$$

$$L_1 = d_1^2 - d_2^2 + x_2^2 - x_1^2 + y_1^2 - y_2^2 \tag{14}$$

$$L_2 = d_2^2 - d_3^2 + x_3^2 - x_2^2 + y_2^2 - y_3^2 \tag{15}$$

The $x$ and $y$ can then be retrieved as follows:

$$x = \frac{L_1 B_2 - L_2 B_1}{B_2 A_1 - B_1 A_2} \tag{16}$$

$$y = \frac{L_2 A_1 - L_1 A_2}{B_2 A_1 - B_1 A_2} \tag{17}$$

## III. Experimental Results

With reference to Fig. 1, $(x_A, y_A)$ is taken as the origin point, i.e. the coordinate is (0, 0). The initial coordinate of the robot is (1, 0), with a heading angle of 90° from the x-axis. The distance from the robot to the node is calculated based on (2) while it moves from (1, 0) to (1, 1), and the corresponding coordinate is then retrieved via trilateration. This procedure is carried out twice, and we denote the first and second trials as Test 1 and Test 2 respectively.

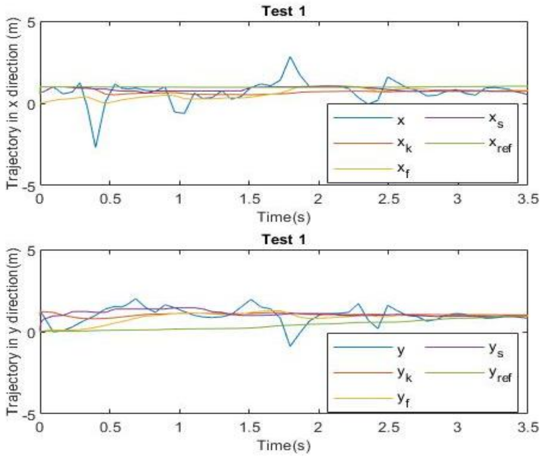


Fig. 4. Trajectories of the robot in $x$ and $y$ directions for Test 1.

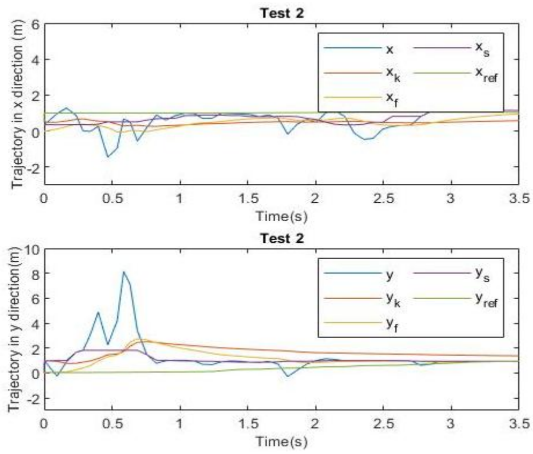


Fig. 5. Trajectories of the robot in $x$ and $y$ directions for Test 2.

The localization of the object based on the proposed method is also compared with trilateration with the raw RSSI values and two other standard approaches, namely Kalman and low pass filter. We write $(x, y)$, $(x_k, y_k)$, $(x_f, y_f)$ and $(x_s, y_s)$ to represent the coordinates calculated from the raw $R$ values, Kalman filter, LPF and the proposed method respectively. The results are presented in Fig. 4 and Fig. 5 where the trajectories presented in x- and y-directions against time for each test. The actual trajectories of the robot, $(x_{\text{ref}}, y_{\text{ref}})$, which were recorded via a camera, are also shown in the figure.

From the figure, it is clearly seen that the raw RSSI data have caused fluctuations in the reading, leading to large localization errors. This is mainly due to multipath effects, propagation loss and interference from the surroundings. It is also observed that all the filtering approaches including the proposed method can alleviate the aforementioned effects. In order to evaluate the performance, the distance errors in $x$ and $y$ directions against time are plotted in Fig. 6 and Fig. 7. It can be observed that as time passes, all errors converge towards zero. The raw RSSI data, as expected, show the highest error with time with very high fluctuations, while the filtered ones show significant reductions in the error. The total error is calculated based on the area under the plots from starting to ending time, and the numerical results are recorded in Table I. Based on the calculated errors, it is clear that the proposed strategy can further reduce the error as compared to the results from the other methods.

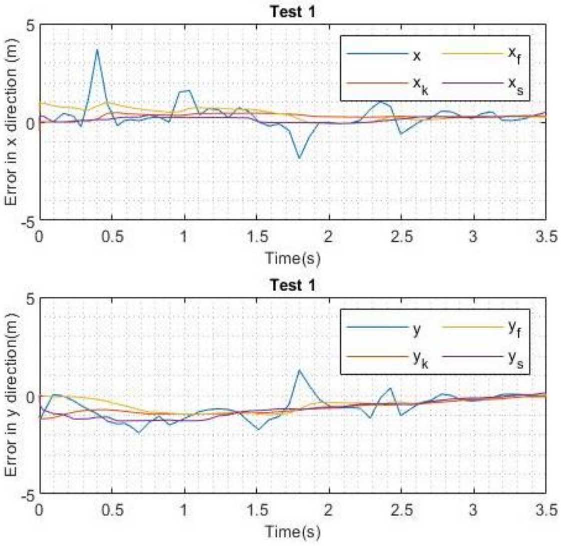


Fig. 6. Distance error in *x* and *y* directions against time for Test 1.

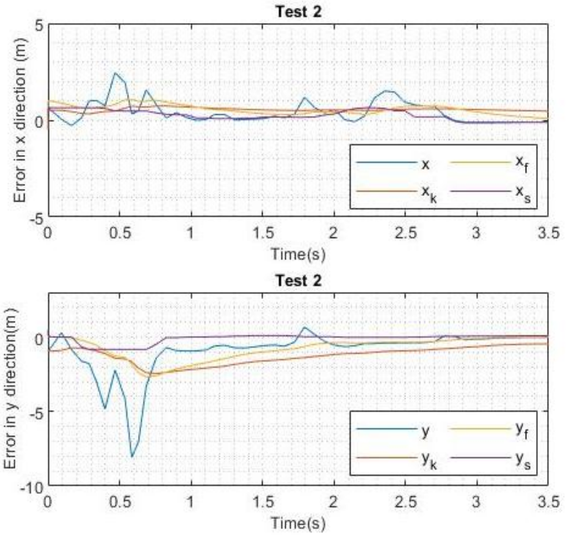


Fig. 7. Distance error in *x* and *y* directions against time for Test 2.

TABLE I: AVERAGE ERROR

| Test | Compensation Duration (s) | | | |
|---|---|---|---|---|
| | Raw Data | Kalman | LPF | Proposed Method |
| 1 | 5.3536 | 4.1898 | 3.8766 | 4.1970 |
| 2 | 6.9921 | 7.5838 | 5.7200 | 4.6192 |
| Average | 6.1729 | 5.8868 | 4.7983 | 4.4081 |

## IV. DISCUSSIONS AND CONCLUSIONS

In this paper, an indoor localization technique for a mobile object using Zigbee-based RSSI is considered. As multipath effects and interference from the surrounding cause notable errors on the RSSI values, the smoothness index to select RSSI values with best quality is proposed. The proposed strategy is evaluated via a simple experiment where the object with a receiver antenna is placed on a wheeled mobile robot moving on a predefined trajectory at a constant speed. The result is also compared with other standard filtering approaches, and the performance is analyzed in terms of position error at each time instance between the starting and ending positions of the object. Experimental results show that the cumulative error can be significantly reduced as compared to the results from other standard approaches.

Future work includes investigations on effective positions of the nodes to provide a smoother distance estimation, possibility to use a dual-directional antenna, and comparison with other artificial intelligence-based methods.

## CONFLICT OF INTEREST

"The authors declare no conflict of interest".

## AUTHOR CONTRIBUTIONS

A. Loganathan and N. S. Ahmad conducted the research; A. Loganathan conducted the experiments, analyzed the data, and wrote the paper; N. S. Ahmad validated the results; all authors had approved the final version.

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